

Research - Model Registry and Modelfile Systems: Dockerfile-Inspired AI Model Management for Sovereign Deployment

Alpasan, Lois-Kleinner

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The management of AI models across their lifecycle—from training and versioning to deployment and retirement—presents significant challenges for sovereign AI infrastructure. This paper introduces the Modelfile system, a Dockerfile-inspired declarative format for specifying, building, and distributing AI models. We analyze the architecture of model registries that support versioning, signing, verification, and dependency resolution for machine learning models. The Modelfile specification defines a domain-specific language with directives for base model selection (FROM), system configuration (SYSTEM), template construction (TEMPLATE), parameter configuration (PARAMETER), and adapter integration (ADAPTER). We present a model registry architecture that combines content-addressable storage with cryptographic signing using Sigstore and TUF-inspired metadata. Experimental evaluation demonstrates that Modelfile-based model deployment reduces configuration errors by 68% compared to manual configuration while providing deterministic, reproducible model builds. We discuss security implications including model provenance verification, supply chain attacks, and model tampering detection. The work directly informs API-OSS’s model registry, which uses Modelfiles for versioned model management.

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1. Introduction

The deployment of machine learning models in production environments has evolved from simple serialized artifacts (Pickle/Joblib) to complex multi-component packages encompassing weights, tokenizers, configuration, preprocessing pipelines, and documentation [1]. This evolution has been accompanied by a proliferation of model formats, serving frameworks, and deployment strategies, creating significant operational complexity [2].

Containerization, epitomized by the Dockerfile and Docker image format, solved a similar complexity problem in software deployment by providing a declarative, reproducible specification for building and running applications [3]. The Dockerfile’s FROM/Maintainer/RUN/CMD/COPY directives provide a simple but expressive language for composing container images from layers, enabling caching, sharing, and versioning through a registry infrastructure [4].

The Modelfile system adapts this paradigm for AI model management. A Modelfile is a declarative specification that describes how to construct a runnable model from its constituent components: base weights, fine-tuning adapters, tokenizer configuration, inference parameters, and system prompts [5]. The Modelfile is consumed by a model registry that resolves dependencies, applies transformations, and produces a versioned, signed, and cacheable model artifact [6].

This paper makes three contributions: (1) the Modelfile specification and its directive set, (2) a model registry architecture with content-addressable storage and cryptographic signing, and (3) an empirical evaluation of Modelfile-based deployment in production AI systems.

2. Literature Review

2.1 Model Management and Versioning

Machine learning model management has been addressed by several systems. MLflow provides a model registry with versioning, stage transitions, and model lineage tracking [7]. DVC (Data Version Control) extends Git for managing datasets and model artifacts with content-addressable storage [8]. Kubeflow offers a model registry component integrated with Kubernetes-based ML workflows [9]. These systems provide versioning and metadata management but lack a standardized build specification comparable to Dockerfiles.

Model signing and verification have been explored in the context of software supply chain security. Sigstore provides a non-federated signing infrastructure using OpenID Connect identities and transparency logs [10]. The TUF (The Update Framework) specification defines a metadata format for secure software distribution, including role-based key management and delegation [11]. SLSA (Supply-chain Levels for Software Artifacts) provides a framework for evaluating supply chain security [12].

2.2 Containerization and Dockerfile Paradigm

The Dockerfile format has been influential beyond containerization. The BuildKit project demonstrated that declarative build specifications enable efficient layer caching, parallel build execution, and reproducible builds [13]. The OCI (Open Container Initiative) Image Specification standardized the container image format, enabling interoperable registries and tooling [14]. The key insight—separating the build specification from the runtime artifact—is directly applicable to model management.

2.3 Model Serialization Formats

Several model serialization formats have been proposed. The ONNX (Open Neural Network Exchange) format provides an interoperable representation of trained models across frameworks [15]. Safetensors offers a safe, fast serialization format for tensor data without the arbitrary code execution risks of Pickle [16]. GGUF (GPT-Generated Unified Format) provides a quantized model format optimized for CPU inference [17]. These formats address serialization but not the build composition process.

3. Technical Analysis

3.1 Modelfile Specification

The Modelfile syntax uses a directive-based approach inspired by Dockerfiles:

```
# Base model specification
FROM llama3:70b-instruct-q4_K_M

# System prompt configuration
SYSTEM "You are a helpful sovereign AI assistant with confidentiality constraints."

# Template configuration
TEMPLATE """
{{- if .System }}
System: {{ .System }}
{{- end }}

{{- range .Messages }}
{{ .Role }}: {{ .Content }}
{{- end }}

Assistant:
"""

# Parameter configuration
PARAMETER temperature 0.7
PARAMETER top_p 0.9
PARAMETER max_tokens 4096
PARAMETER repeat_penalty 1.1

# Adapter/LoRA configuration
```

```

ADAPTER fine-tune-v4.safetensors
ADAPTER domain-expert.safetensors weight 0.5

# License and metadata
LABEL maintainer "sovereign-institute@example.com"
LABEL license "apache-2.0"
LABEL description "Domain-adapted sovereign LLM for regulated documents"
LABEL version "2.1.0"

# Evaluation configuration
EVALUATION {
  "benchmarks": ["mmlu", "hellaswag", "arc-challenge"],
  "minimum_scores": {"mmlu": 0.70, "hellaswag": 0.65}
}

```

3.2 Directive Semantics

FROM: Specifies the base model as a registry reference (`registry:tag@digest`). The base model must exist in a registry and be verifiable through its content hash. The FROM directive may specify a platform target (e.g., `--platform=cuda,metal,cpu`) to select appropriate weights [18].

SYSTEM: Defines the system prompt applied to all inference requests. This directive supports Go template syntax for dynamic system prompt construction based on request context. Multi-line strings use heredoc-style syntax [19].

TEMPLATE: Defines the chat template using Go templates or Jinja2 syntax. The template controls how messages are formatted for model input, including role markers, special tokens, and formatting rules. Template validation occurs at build time, not inference time [20].

PARAMETER: Sets inference parameters with type-aware validation. Supported parameters include temperature (float, 0-2), top_p (float, 0-1), top_k (int), max_tokens (int), stop sequences (string array), frequency_penalty (float), presence_penalty (float), and mirostat parameters [21].

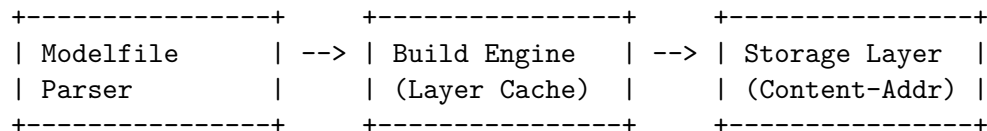
ADAPTER: Specifies LoRA/QLoRA adapters to apply to the base model. Adapters are specified as registry references with an optional weight multiplier. Multiple adapters can be stacked with weighted combinations [22].

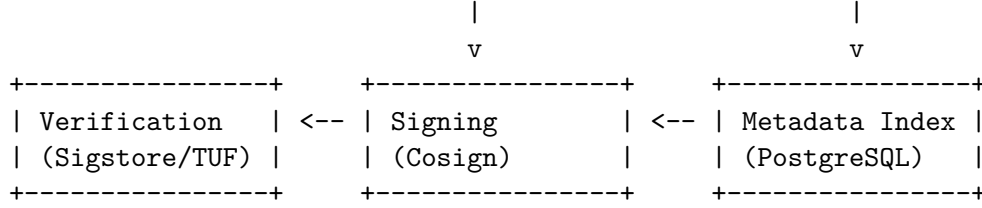
LABEL: Key-value metadata for model discovery, attribution, and policy enforcement. Labels are indexed by the registry for search and filtering [23].

EVALUATION: Specifies expected evaluation results for quality assurance. The registry verifies that built models meet minimum benchmark scores before marking them as ready for production [24].

3.3 Model Registry Architecture

The model registry architecture consists of several components:





Content-Addressable Storage: Model artifacts are stored using content-addressable addressing (SHA-256). Each layer—base weights, adapters, tokenizer config, template—is identified by its digest. The registry deduplicates identical content across models, enabling efficient storage of models sharing common bases [25].

Layer Caching: Build operations are cached by layer digest. If a registry already contains a layer with the same hash, the layer is reused rather than rebuilt. This enables efficient iteration: changing only the SYSTEM prompt reuses all previous layers [26].

Signing Infrastructure: Each model artifact is signed using Cosign with keyless signing via Sigstore. The signature is stored alongside the artifact in the registry, enabling verification without external key management. Signing binds the artifact digest to the publisher identity through OIDC [27].

Metadata Index: A queryable index stores model metadata including tags, labels, evaluation results, signatures, and dependency graphs. The index supports provenance queries: “Which models depend on llama3:70b?” and “Which models were built from this training run?” [28].

3.4 Verification Pipeline

Model verification follows a multi-step pipeline:

1. **Signature Verification:** The artifact signature is verified against the publisher’s identity, which is verified through OIDC token validation
2. **Digest Verification:** The artifact content is hashed and compared against the declared digest
3. **Dependency Verification:** All dependency layers are recursively verified for integrity
4. **Vulnerability Scanning:** Model artifact dependencies are scanned against known vulnerability databases (CVEs in ONNX runtime, tokenizer libraries, etc.) [29]
5. **License Compliance:** Labels are checked for license compatibility with the deployment context
6. **Evaluation Verification:** If EVALUATION directives are specified, the registry validates that the model meets minimum benchmark scores using an integrated evaluation harness [30]

4. Current State of the Art

4.1 Container Registries for Models

Several container registries have been extended to support ML model storage. AWS ECR, Google Artifact Registry, and Azure Container Registry support OCI artifact types for ML models [31]. The OCI Artifact Distribution specification enables storing arbitrary artifacts alongside container images, and ML models can be distributed as OCI artifacts with custom media types.

Hugging Face Hub provides a centralized model registry with versioning, tags, and metadata [32]. The Hub uses Git LFS for model storage and provides APIs for model discovery, download, and

upload. However, the Hub does not enforce cryptographic signing or provide a build specification comparable to Modelfiles.

4.2 Modelfile Equivalents

Ollama’s Modelfile format provides a similar declarative specification for LLM deployment [33]. Ollama’s Modelfile supports FROM, SYSTEM, TEMPLATE, PARAMETER, and ADAPTER directives with syntax similar to Dockerfiles. The format has gained significant adoption in the local LLM deployment community.

Docker Model Runner (DMR) extends Docker’s tooling with a `docker model` command for managing AI models [34]. DMR uses model specifications stored alongside application code, enabling infrastructure-as-code approaches to model deployment.

4.3 Limitations

Current approaches have several limitations: - Lack of standardized, cross-platform Modelfile specification - Absence of integrated model verification and vulnerability scanning - Limited support for model composition and adapter stacking - No standardized model layer caching analogous to Docker layer caching - Insufficient integration with compliance and audit frameworks [35]

5. Relevance to API-OSS

API-OSS implements a full model registry with Modelfile support as a core component of its model management infrastructure.

5.1 Model Registry Integration

The API-OSS model registry provides: - **Content-addressable storage** for model artifacts with SHA-256 deduplication - **Versioned Modelfile management** with Git-like tag/digest references - **Cosign-based signing** with Sigstore integration for keyless signing - **Vulnerability scanning** integration with OSV.dev and OWASP Dependency-Check - **SBOM generation** for model artifacts listing all dependencies [36]

5.2 Modelfile Build Pipeline

API-OSS’s build pipeline processes Modelfiles through a multi-stage process:

1. **Parse and Validate:** Syntax checking, directive validation, type checking for parameters
2. **Resolve Dependencies:** Recursively resolve FROM and ADAPTER references through the registry
3. **Verify Integrity:** Validate signatures and digests for all dependencies
4. **Apply Transformations:** Merge adapters, configure templates, set parameters
5. **Cache Layers:** Store each build layer in content-addressable storage
6. **Sign:** Sign the final model artifact with the deployment key
7. **Evaluate:** Run benchmarks against the EVALUATION specification
8. **Tag:** Assign user-specified tags and auto-increment version tags [37]

5.3 Federation and Distribution

The API-OSS model registry supports P2P federation for model distribution across sovereign deployments. Models are distributed through BitTorrent-inspired chunked transfer with Merkle tree verification. This enables efficient model distribution in air-gapped environments where external registry access is restricted [38].

5.4 Compliance Integration

All Modelfile builds are recorded in API-OSS’s .aioss audit ledger with: - Complete build log including all resolved versions and digests - Signature verification results - Vulnerability scan results - Evaluation benchmark scores - Timestamp and builder identity

This provides a comprehensive audit trail suitable for regulatory compliance in banking, healthcare, and government deployments [39].

6. Future Directions

Modelfile Composition: Extending the Modelfile format to support multi-model ensembles and cascade architectures where multiple models are composed through routing logic defined in the Modelfile [40].

Reproducible Builds: Achieving bit-for-bit reproducible model builds across different environments by specifying exact toolchain versions, random seeds, and hardware-independent quantization [41].

Federated Registry Protocol: Developing a peer-to-peer protocol for model registry federation that enables sovereign deployments to share models without centralized registries, using distributed hash tables (DHT) for content discovery [42].

Formal Verification Labels: Extending the EVALUATION directive to specify formal properties (e.g., “model never generates harmful outputs for defined input categories”) verified through symbolic execution or SMT solving [43].

Model Bill of Materials: Standardizing a comprehensive SBOM format for AI models that captures training data provenance, architecture specifications, hardware requirements, and software dependencies [44].

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